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Habitat-based spatial prediction of human-elephant conflict risk in Minas, Riau, Indonesia

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Abstract. *Syahran FN, Rahman DA, Santosa Y. 2025. Habitat-based spatial prediction of human-elephant conflict risk in Minas, Riau, Indonesia. Biodiversitas 26: 4465-4478.* Human-Elephant Conflict (HEC) presents a pressing threat to the endangered Sumatran elephant (*Elephas maximus sumatranus*) in Riau, Indonesia. This study utilized Maximum Entropy (MaxEnt) modeling to predict HEC risk zones in Minas, focusing on a small subpopulation of 11 GPS-collared elephants. Conflict occurrence data from 2020-2022 were compiled from validated reports by the Riau Natural Resources Conservation Agency (BBKSDA) and Global Positioning System (GPS) movement records. Fourteen environmental variables were initially considered, and multicollinearity analysis reduced these to eleven key predictors. MaxEnt was run using 25 cross-validation replicates, achieving excellent performance (AUC: 0.958). Proximity to open land (40.9% contribution), industrial forest plantations (22.8%), settlements (9.2%), roads (8.8%), and oil palm plantations (8.3%) emerged as the strongest predictors. Conflict probability peaked within 0-2 km of anthropogenic features, confirming the critical role of disturbed habitats. High- to very-high-risk zones (>70% probability) covered 19.94 km² (1.76% of the landscape) and were identified as priority areas for intervention, while a moderate-risk zone of 221.32 km² (19.48%) requires targeted monitoring. Low and minimal-risk zones dominated, spanning over 1,000 km² (>80%). These spatial predictions offer actionable insights for conservation planning by directly linking risk zones to mitigation needs. Strategies such as establishing buffer crops, strengthening community-based patrols, and developing early warning systems should be prioritized in high-risk areas. At the same time, habitat connectivity and ecological restoration are crucial for mitigating long-term conflict pressure. Overall, this study advances HEC modeling in Sumatra by combining empirical conflict records with predictive mapping, offering a practical framework to guide evidence-based management and promote human-elephant coexistence in fragmented tropical landscapes.

Keywords: Fragmented habitat, MaxEnt modeling, species conservation, Sumatran elephant, wildlife management

INTRODUCTION

Human-Elephant Conflict (HEC) remains a major conservation challenge in Indonesia. HEC poses a significant threat to the endangered Sumatran elephant (*Elephas maximus sumatranus* Temminck, 1847), primarily driven by habitat loss and fragmentation resulting from land conversion and plantation expansion (Kuswanda et al. 2022; Nurmaliah et al. 2024). Between 2012 and 2017, Aceh Province recorded 262 HEC incidents, resulting in eight human deaths and 45 elephant fatalities (Qomariah et al. 2019). While in Lampung, data from 2015 to 2021 show similar patterns (Khairani et al. 2023). Although recent studies have examined elephant ecology in human-modified landscapes, detailed records of severe casualties remain limited (Hadinata et al. 2023; Imron et al. 2023; Ningrum et al. 2023). These ongoing conflicts have accelerated population declines, with fewer than 1,400 Sumatran elephants estimated to remain in the wild (Pirmansyah et al. 2024).

Sumatran elephants are ecological engineers, shaping forest structure through seed dispersal, gap creation, and vegetation dynamics (Lubis et al. 2023; Ong et al. 2023). Their reliance on low-disturbance, semi-natural habitats underscores the importance of maintaining habitat connectivity (Imron et al. 2023). However, Sumatra faces one of the world's highest deforestation rates, with the rapid conversion of forests to plantations severely reducing available habitat (Kautsar and Halil 2018). Habitat loss not only restricts elephant ranges but also intensifies conflict as elephants are forced into agricultural areas (Nurmaliah et al. 2024). Plantation expansion, encroachment, and overlapping land tenure contribute to corridor disruption and weak enforcement of land-use regulations (Poor et al. 2019). In Aceh, for example, elephant herds increasingly range beyond traditional habitats, with heightened sensory acuity enabling them to detect crops over long distances (Ball et al. 2022; Abdullah et al. 2025).

Within Southeast Asia, SDMs have been increasingly applied to elephant conservation but remain underexplored in relation to HEC. In Thailand, Kitratporn and Takeuchi (2022) combined land-use and socio-economic data to map conflict risk zones, whereas in Myanmar, Leimgruber et al. (2003) examined how agricultural expansion influenced elephant distribution. In Peninsular Malaysia, Campos-Arceiz et al. (2009) highlighted the role of oil palm landscapes in elevating conflict probabilities. In Sri Lanka, Jayakody et al. (2024) used nationwide HEC modeling with MaxEnt and a low-resolution raster. In Indonesia, Kuswanda et al. (2022) employed habitat modeling to assess elephant occupancy; however, few studies have explicitly developed spatially explicit HEC risk models that integrate both ecological and anthropogenic predictors. Its high predictive accuracy and probabilistic framework make it well-suited for developing adaptive HEC mitigation strategies in landscapes undergoing rapid anthropogenic change (Zvidzai et al. 2023; Johansson et al. 2025).

Global Positioning System (GPS) collars have been used to monitor the movements of Sumatran elephants, including the "Group of 11" or "Minas-elephant group", which comprises approximately 11 individuals, as the number may vary slightly over time. Their range lies within the Sultan Syarif Hasyim Grand Forest Park (TSSH), an area under high human pressure due to tourism and the use of non-timber products (Lestari et al. 2022). The habitat is fragmented and isolated, with nearby subpopulations only in Giam Siak Kecil and Tesso Nilo National Park (Sulistyawan et al. 2017; Kuswanda et al. 2022). Moreover, TSSH's small forest patch and weak legal protection pose serious challenges for elephant conservation (Poor et al. 2019).

This study examines the key habitat and anthropogenic factors that influence the spatial distribution of HEC in the fragmented landscape of Minas, Riau. The hypothesis is that HEC is more likely to occur near human infrastructure, such as roads, settlements, and agricultural areas, as well as in areas with degraded habitat conditions, including low forest cover and high fragmentation. A spatially explicit HEC risk model is developed using the MaxEnt approach, based on GPS collar data and environmental spatial layers, to test these hypotheses. Model performance is evaluated using standard metrics, including Area Under the Curve (AUC) and variable contributions. The study has two main objectives: (i) to identify the key habitat variables influencing HEC distribution, (ii) to construct a predictive model of HEC hotspots in the Minas landscape. The findings will support more effective conflict mitigation and habitat management strategies for the conservation of Sumatran elephants.

MATERIALS AND METHODS

Study area

The study area encompasses Siak District, Kampar District, and Pekanbaru City in Riau Province, Indonesia. It is situated at coordinates 0°45′ South Latitude and 101°27′ East Longitude, covering a total area of approximately 1,138.94 km² (Figure 1). Administratively, this region falls under the jurisdiction of the Production Forest Management Unit (KPHP) Minas, and Large Center for Natural Resources Conservation or *Balai Besar Konservasi Sumber Daya Alam* (BBKSDA) Riau handles the elephant conservation management. The landscape is primarily lowland with a gently undulating topography, ranging in elevation from 0 to 200 meters above sea level. A lowland tropical rainforest ecosystem characterizes this area.

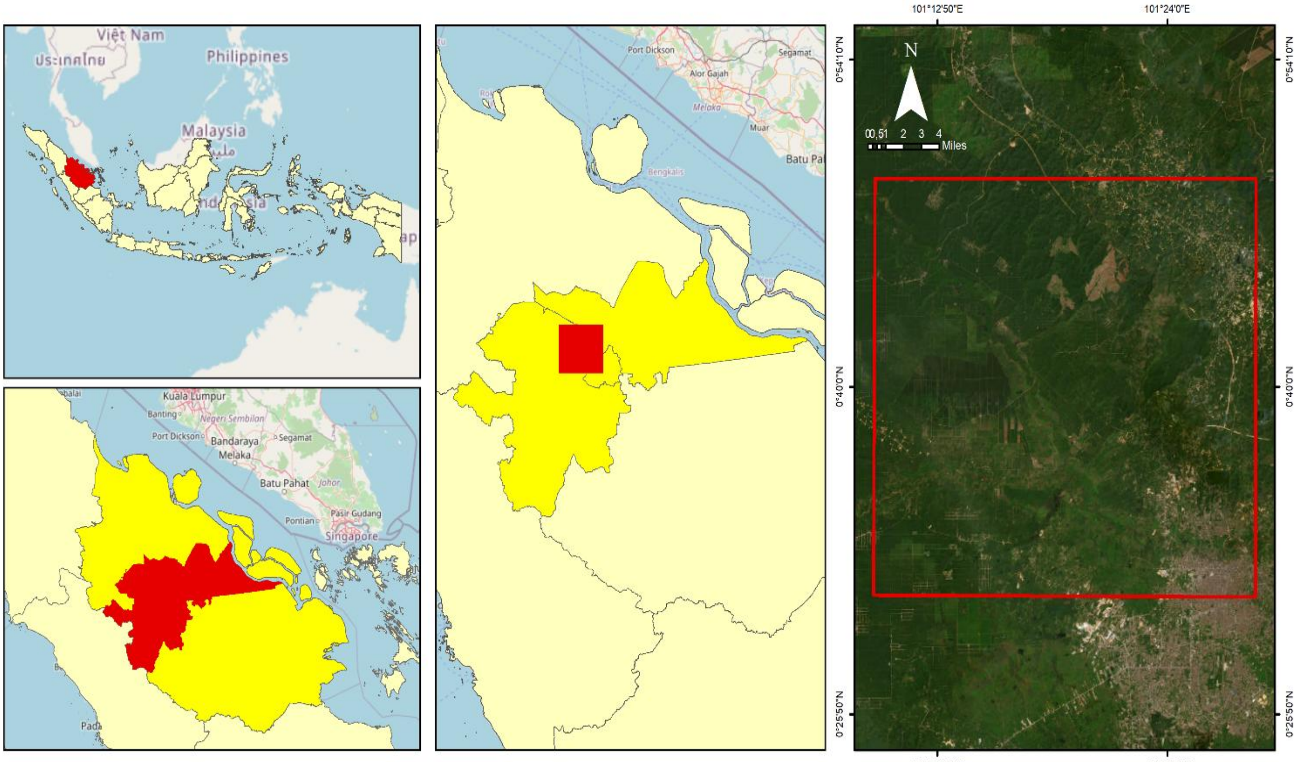


Figure 1. The location of this research is Siak District, Kampar District, and Pekanbaru City in Riau Province, Indonesia

Data collection

HEC incidents

The data collected in this study consisted of primary and secondary data. Primary data were obtained through direct fieldwork activities, including structured observations, semi-structured interviews with mahouts (elephant handlers) from the Minas Elephant Training Center (PLG Minas), and selective ground-truthing of reported conflict locations. Mahouts were chosen for their direct involvement in driving back wild elephants, providing first-hand knowledge of conflict areas. Data were gathered until no new information emerged and were verified by site visits, GPS recording, and land-cover assessment. Where access was limited, verification relied on GPS-collar data to ensure spatial and temporal accuracy.

Secondary data was obtained by reviewing official reports and field documents from authoritative agencies operating in the region. Specifically, GPS-collar data, including geographic coordinates and timestamps, were provided by the Biodiversity Conservation Agency (BKSDA) of Riau Province, covering the period from January 23, 2020, to January 20, 2021. These datasets were complemented by georeferenced conflict reports submitted by local field officers. These records formed the basis for identifying "conflict points", defined in this study as spatial coordinates where documented elephant interactions with human activities occurred, such as crop raiding, property damage, or elephant presence near settlements.

Environmental variables

The selection of environmental variables in this modeling was based on the ecological characteristics of a subpopulation of Sumatran elephants in the Minas region, Riau. This area represents one of the key habitats for the species, which is under considerable pressure due to the expansion of palm oil plantations, mining activities, infrastructure development, and forest fragmentation. Fourteen environmental variables were used in the spatial analysis to implement the MaxEnt modeling approach. Natural factors, such as proximity to forested areas, water availability, low elevation, and gentle slopes, are critical in determining habitat suitability (Sulistyawan et al. 2017; Kuswanda et al. 2022). The study by Rahman et al. (2022) in Sumatra demonstrates that Normalized Difference Vegetation Index (NDVI) contributes to species distribution modeling, serving as a biotic indicator and an essential habitat component for large mammals. Climatic variables (humidity and rainfall) are also used as biophysical habitat factors, given their influence on the availability of water and vegetation in an area.

Anthropogenic factors included the distance from settlements and roads, which are commonly associated with increased conflict due to the overlap of human activity and elephant movement, particularly during seasonal migrations (Kuswanda et al. 2022). Rendana et al. (2023) have shown that elephants prefer densely forested areas with slopes less than 20° and avoid locations with intensive human activity. Open land and shrubland are included as transitional zones frequently traversed or temporarily used by elephants navigating fragmented habitats. These land cover types often serve as ecological buffers between core forest areas and developed zones, where elephants have been observed moving, foraging, or resting, particularly in response to habitat fragmentation or anthropogenic pressures (Qomariah et al. 2019; Fikri et al. 2023). Collectively, while these variables may not be specific to either species, they are critical to include in HEC risk modeling, as they enhance the overall accuracy and robustness of the predictive framework (Table 1).

The environmental variables in this study were managed by integrating spatial data from various online sources. Most of the distance-based variables, such as distance from open land, settlements, plantations, industrial timber estates (HTI), roads, forests, shrublands, agricultural areas, and water bodies, were derived from vector data obtained through the Ministry of Environment and Forestry's portal (https://sigap.menlhk.go.id/) and the Landforms of Indonesia portal (https://tanahair.indonesia.go.id/portal-web/). These vector data were typically shapefiles (SHP), containing spatial boundary information for each land cover category or infrastructure feature.

Once the vector data were compiled and pre-processed, spatial analysis was conducted using GIS software (ArcGIS 10.8) to generate distance variables. A commonly used method was Euclidean Distance analysis, which calculates the shortest distance from each pixel or observation point to specific spatial features. This analysis was a distance raster, from which values were extracted at observation points or used directly in modelling. The biophysical variables consisted of the (NDVI) and humidity (derived from Landsat 8 OLI TIRS imagery via USGS), precipitation (from CHIRPS data), as well as elevation and slope (obtained from DEMNAS). Subsequently, each raster was standardized to a uniform spatial resolution (e.g., 30 meters), clipped to the study area, and resampled as necessary to ensure consistency. All vector and raster spatial data were standardized to a uniform coordinate system (UTM WGS 84 Zone 47N) for the study area. The final step involved converting all raster (TIFF) layers into ASCII (.asc) format, which is compatible with MaxEnt software, using tools such as *Raster to ASCII* in ArcToolbox. This standardization and data processing step was critical to ensure spatial alignment and analytical validity in species or habitat distribution studies.

Data analysis

This study applied the MaxEnt approach to model HEC risk using conflict records and environmental variables. Data preparation included partitioning and variable selection, followed by model execution to predict risk areas. Model performance was evaluated, and the final outputs were used to map and identify HEC hotspots, as outlined in the research flowchart (Figure 2).

Data pre-processing

Data preprocessing was a key step before modeling. Environmental layers were resampled to a standardized resolution, and conflict data were filtered to ensure accurate coordinates, remove duplicates, and exclude records outside the study area (Velazco et al. 2022). To reduce spatial and temporal biases in interview-based conflict data, reported incidents were validated against GPS-collar movement records. Only events aligned in both space and time with elephant locations were retained as presence data, while background points were randomly sampled across the study area. This approach minimized recall bias and strengthened the ecological validity of the model, consistent with recommendations for addressing spatial bias in presence-only species distribution models (Fourcade et al. 2014). To prevent model overfitting, presence data were spatially thinned using a grid-based filter, and multicollinearity among predictors (e.g., land use/land cover) was tested and reduced. Limitations remain, however, including uncertainties in land cover classification, potential bias in qualitative data, and the absence of explicit temporal dynamics. These factors should be considered when interpreting model outputs.

Testing for variable correlation

The initial stage in modelling involves the selection of predictor variables. The aim is to identify variables used in the modelling process. One common approach to selecting environmental variables is to conduct a multicollinearity test on all potential predictors. Multicollinearity refers to a linear relationship or high correlation among predictor variables. This test is crucial for identifying linear dependencies between variables, ensuring that the predictors used in the model do not influence one another (Feng et al. 2019). The multicollinearity test was performed using the olsrr package in R-Statistics. Variables exhibiting a high Pearson correlation coefficient (|r|>0.7) were eliminated to ensure all predictors included in the model are independent (Dormann et al. 2013).

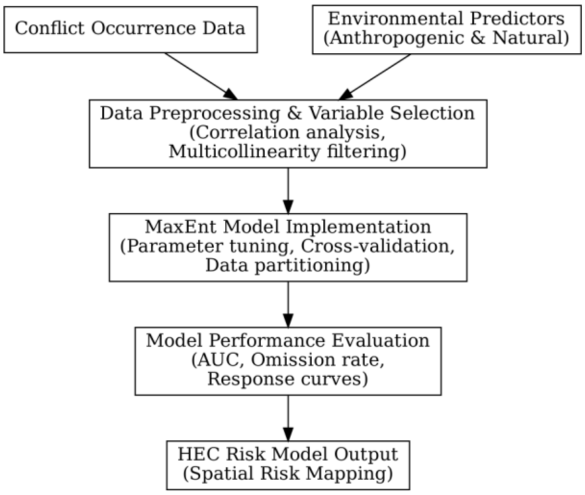


Figure 2. Research flowchart

Table 1. Types of data and methods of data collection

Environmental variable	Source	Data type / Resolution	Preprocessing
Distance from open land	Field observation and Land Cover (https://sigap.menlhk.go.id/)	Vector to raster / 30m	Euclidean distance, converted to ASCII format, and clipped to AOI
Distance from the settlement	Field observation and Landforms of Indonesia (https://tanahair.indonesia.go.id/portal-web/)	Vector to raster / 30m	Euclidean distance, converted to ASCII format, and clipped to AOI
Distance from the plantation	Field observation and Land Cover https://sigap.menlhk.go.id/	Vector to raster / 30m	Euclidean distance, converted to ASCII format, and clipped to AOI
Distance from industrial forest (HTI)	Field observation and Land Cover https://sigap.menlhk.go.id/	Vector to raster / 30m	Euclidean distance, converted to ASCII format, and clipped to AOI
Distance from the road	Field observation and Landforms of Indonesia (https://tanahair.indonesia.go.id/portal-web/)	Vector to raster / 30m	Euclidean distance, converted to ASCII format, and clipped to AOI
Distance from the forest	Field observation and Landforms of Indonesia (https://sigap.menlhk.go.id/)	Vector to raster / 30m	Euclidean distance, converted to ASCII format, and clipped to AOI
Distance from shrubland	Field observation and Landforms of Indonesia (https://sigap.menlhk.go.id/)	Vector to raster / 30m	Euclidean distance, converted to ASCII format, and clipped to AOI
Distance from the agricultural area	Field observation and Landforms of Indonesia (https://sigap.menlhk.go.id/)	Vector to raster / 30m	Euclidean distance, converted to ASCII format, and clipped to AOI
Distance from the water body	Field observation and Landforms of Indonesia (https://sigap.menlhk.go.id/)	Vector to raster / 30m	Euclidean distance, converted to ASCII format, and clipped to AOI
NDVI	Landsat 8 OLI TIRS-USGS (https://earthexplorer.usgs.gov/)	Raster / 15m resampling to 30m	Raster Calculator; Reclassified and converted to ASCII format; Clipped to AOI
Humidity	Landsat 8 OLI TIRS-USGS (https://earthexplorer.usgs.gov/)	Raster / 15m resampling to 30m	Raster Calculator; Reclassified, converted to ASCII format; and clipped to AOI
Rainfall	Chirps (https://www.chc.ucsb.edu/data/chirps)	Raster / 5.5km resampling to 30m	Interpolation, Raster Calculator, Reclassified, converted to ASCII format, and Clipped to AOI.
Elevation	DEMNAS-Landforms of Indonesia (https://tanahair.indonesia.go.id/portal-web/)	Raster / 8m resampling to 30m	Reclassified, converted to ASCII format, and clipped to AOI
Slope	DEMNAS-Landforms of Indonesia (https://tanahair.indonesia.go.id/portal-web/)	Raster / 8m resampling to 30m	Reclassified, converted to ASCII format, and clipped to AOI

Model processing

This study employed the Maximum Entropy (MaxEnt) method, a widely used species distribution modeling tool that predicts distributions from presence-only data and environmental variables (Liu et al. 2007; Phillips et al. 2017). MaxEnt is particularly suitable when absence data are unavailable or unreliable. Model calibration was performed with a regularization multiplier of 1.0 to balance complexity and overfitting (Phillips et al. 2006). The algorithm was run for up to 5,000 iterations with a convergence threshold of 0.00001 to ensure stability. To test robustness, 25 replicate runs were generated using the sub-sample approach, with 25% of the data randomly set aside for testing in each run. Variable importance was further assessed through Jackknife tests, which evaluated the individual and combined contributions of environmental predictors (Merow et al. 2013).

Model evaluation

The MaxEnt model's performance was assessed using two key indicators: the Area Under the Curve (AUC) and the Average Omission Rate (OR). AUC measures the model's ability to distinguish presence from absence (or pseudoabsence), where values >0.75 indicate reliable performance (Elith et al. 2011; Peterson et al. 2011). OR quantifies the proportion of presence records misclassified as absences and is commonly paired with AUC in presence-only models (Phillips et al. 2006; Pearson et al. 2007). Together, these metrics guided the selection of the best-performing model for HEC risk mapping.

In addition, confusion matrix-based metrics were applied to provide a detailed accuracy assessment, including Overall Accuracy (OA), User Accuracy (UA/precision), and Producer Accuracy (PA/recall). The kappa coefficient (κ) was also calculated to measure agreement beyond chance, a standard approach in thematic mapping accuracy evaluations (Foody 2002; Stehman and Foody 2019). The formulas are as follows:

Overall Accuracy (OA):

$$OA = \frac{TP + TN}{\sum N}$$

User accuracy (Precision):

$$Conflict\ area = \frac{TP}{TP + FP}$$

$$non - conflict\ area = \frac{TN}{TN + FN}$$

Producer accuracy (Recall):

$$\text{Conflict area (Sensitivity)} = \frac{TP}{TP + FN}$$

$$\text{Non} - \text{conflict area (Specificity)} = \frac{TN}{TN + FP}$$

Kappa coefficient:

$$\text{K} = \frac{Po - Pe}{1 - Pe}\text{; where } Po = \frac{TP - TN}{N}$$

$$Pe = \frac{(TN + FP)(TP + FN)(FN + TN)(FP + TN)}{N^2}$$

Notation descriptions: TP (True Positive): Number of conflict areas correctly predicted as conflict; TN (True Negative): Number of non-conflict areas correctly predicted as non-conflict; FP (False Positive): Number of non-conflict areas incorrectly predicted as conflict; FN (False Negative): Number of conflict areas incorrectly predicted as non-conflict; N: Total number of observations; P_o (Observed Agreement): Proportion of all observations correctly classified; P_e (Expected Agreement by Chance): Probability of agreement expected by random chance.

Kappa Coefficient value interpretation (Foody 2002): <0.00: Poor agreement (worse than chance); 0.00-0.20: Slight agreement; 0.21-0.40: Fair agreement; 0.41-0.60: Moderate agreement; 0.61-0.80: Substantial agreement; 0.81-1.00: Almost perfect agreement.

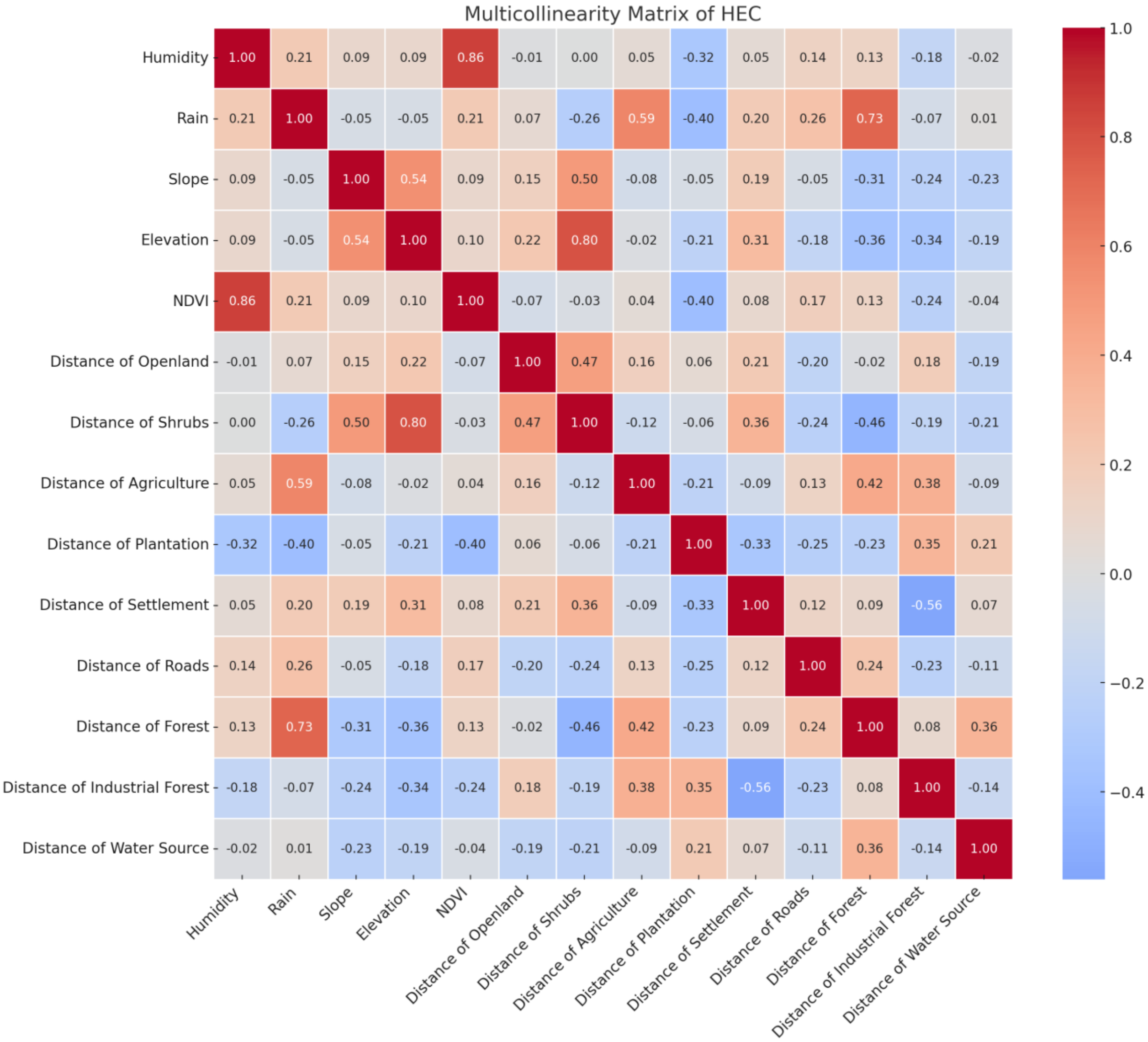
Variable importance analysis

The role of environmental predictors in shaping HEC probability was evaluated through two MaxEnt metrics: percent contribution and permutation importance. Percent contribution indicates the relative gain provided by each variable during model training but can be affected by the order of inclusion. Permutation importance, on the other hand, measures the reduction in model accuracy when variable values are randomly permuted, thereby reflecting their actual influence in the final model (Phillips et al. 2006). Compared to percent contribution, permutation importance is generally regarded as a more reliable measure for interpreting predictor effects in species distribution models.

RESULTS AND DISCUSSION

Multicollinearity among the variables

Based on the correlation matrix (Figure 3), some variables exhibited high pairwise correlations, particularly between Moisture and NDVI (r: 0.86), Altitude and Shrub Distance (r: 0.80), and Rain and Forest Distance (r: 0.73). To reduce redundancy and maintain model simplicity, NDVI was retained due to its direct ecological relevance to vegetation structure, while moisture was excluded from the final model. Similarly, rainfall was chosen as a more comprehensive representation of climatic factors than distance to forest. Elevation was retained over distance to the bush, as it serves as a proxy for topography influencing habitat distribution. Variables with moderate to low correlations (|r|<0.7), such as distance to water sources, roads, and plantations, were included due to their unique spatial influence on elephant movements. This variable selection process enhances the robustness and readability of the MaxEnt model by minimizing the risk of bias associated with multicollinearity.



	Humidity	Rain	Slope	Elevation	NDVI	Distance of Openland	Distance of Shrubs	Distance of Agriculture	Distance of Plantation	Distance of Settlement	Distance of Roads	Distance of Forest	Distance of Industrial Forest	Distance of Water Source
Humidity	1.00	0.21	0.09	0.09	0.86	-0.01	0.00	0.05	-0.32	0.05	0.14	0.13	-0.18	-0.02
Rain	0.21	1.00	-0.05	-0.05	0.21	0.07	-0.26	0.59	-0.40	0.20	0.26	0.73	-0.07	0.01
Slope	0.09	-0.05	1.00	0.54	0.09	0.15	0.50	-0.08	-0.05	0.19	-0.05	-0.31	-0.24	-0.23
Elevation	0.09	-0.05	0.54	1.00	0.10	0.22	0.80	-0.02	-0.21	0.31	-0.18	-0.36	-0.34	-0.19
NDVI	0.86	0.21	0.09	0.10	1.00	-0.07	-0.03	0.04	-0.40	0.08	0.17	0.13	-0.24	-0.04
Distance of Openland	-0.01	0.07	0.15	0.22	-0.07	1.00	0.47	0.16	0.06	0.21	-0.20	-0.02	0.18	-0.19
Distance of Shrubs	0.00	-0.26	0.50	0.80	-0.03	0.47	1.00	-0.12	-0.06	0.36	-0.24	-0.46	-0.19	-0.21
Distance of Agriculture	0.05	0.59	-0.08	-0.02	0.04	0.16	-0.12	1.00	-0.21	-0.09	0.13	0.42	0.38	-0.09
Distance of Plantation	-0.32	-0.40	-0.05	-0.21	-0.40	0.06	-0.06	-0.21	1.00	-0.33	-0.25	-0.23	0.35	0.21
Distance of Settlement	0.05	0.20	0.19	0.31	0.08	0.21	0.36	-0.09	-0.33	1.00	0.12	0.09	-0.56	0.07
Distance of Roads	0.14	0.26	-0.05	-0.18	0.17	-0.20	-0.24	0.13	-0.25	0.12	1.00	0.24	-0.23	-0.11
Distance of Forest	0.13	0.73	-0.31	-0.36	0.13	-0.02	-0.46	0.42	-0.23	0.09	0.24	1.00	0.08	0.36
Distance of Industrial Forest	-0.18	-0.07	-0.24	-0.34	-0.24	0.18	-0.19	0.38	0.35	-0.56	-0.23	0.08	1.00	-0.14
Distance of Water Source	-0.02	0.01	-0.23	-0.19	-0.04	-0.19	-0.21	-0.09	0.21	0.07	-0.11	0.36	-0.14	1.00

Figure 3. Pearson correlation analysis of fourteen environmental variables revealed strong associations, notably between elevation and slope, and among settlement, plantation, and road proximity. These results, visualized in a heatmap (ranging from -1 to +1), guided the selection of independent predictors to avoid redundancy and improve model robustness

MaxEnt prediction evaluation and validation

The predictive performance of the HEC distribution model was assessed using multiple standard validation techniques. The primary method employed was the ROC curve, with the AUC serving as the principal indicator of accuracy. The model yielded an AUC of 0.958 (Figure 4), indicating excellent discriminatory capability in distinguishing between conflict and non-conflict areas. According to established benchmarks, AUC values above 0.9 represent high predictive performance (Peterson et al. 2011). The ROC-AUC method was selected for its objectivity and independence from arbitrary threshold settings (Lobo et al. 2008). In addition to AUC, the model's omission rate was examined across 25 replicates, ranging from 0.10 to 0.15, indicating a low false-negative rate and an intense spatial match between predicted risk areas and known HEC locations (Figure 4). The ROC curve also consistently showed high sensitivity across varying specificity levels, reinforcing the model's robustness in identifying true conflict-prone zones. These performance metrics are commonly used in species distribution modelling to assess the strength of predictions, especially when only presence data are available (Elith et al. 2006; Pearson et al. 2007).

The confusion matrix (Figure 5) analysis revealed that the model achieved an overall accuracy of 88.46% with a kappa coefficient of 0.77, indicating substantial agreement between predicted and observed values. Detailed results in Table 2 demonstrate high precision (94.29%) for conflict areas and strong specificity (94.73%) for non-conflict regions. In comparison, sensitivity for conflict zones (82.50%) was comparatively lower, suggesting that some conflict-prone sites were under-detected.

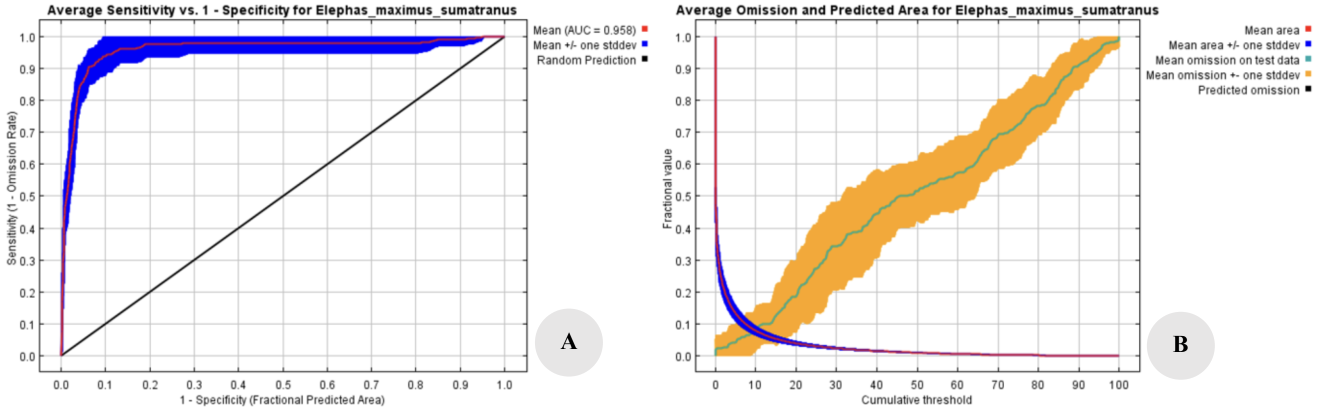


Figure 4. A. Average AUC value of the HEC distribution model; B. Average Omission Rate and predicted area plot of the HEC distribution model. The x-axis shows 1-specificity, and the y-axis shows sensitivity. The model achieved an AUC of 0.958, indicating excellent predictive performance with high discrimination between conflict and non-conflict zones

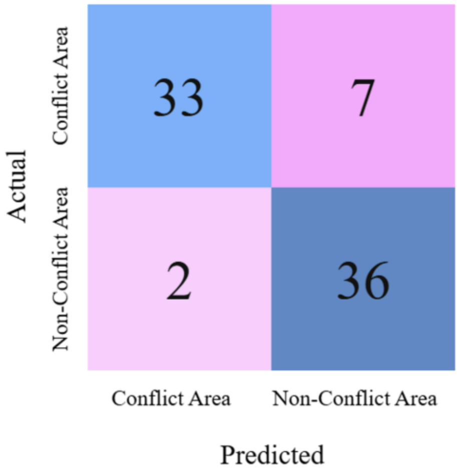


Figure 5. Confusion matrix showing the classification performance of the HEC risk model. The model correctly identified 33 conflict sites (True Positives) and 36 non-conflict sites (True Negatives), while misclassifying 7 conflict sites as non-conflict (False Negatives) and two non-conflict sites as conflict (False Positives)

These results align with recent studies on Sumatran elephants that also reported strong predictive performance in spatial models (Table 2). Imron et al. (2023) found sensitivity and specificity values of 0.76 and 0.68 using 10-fold cross-validation, while Rendana et al. (2023) achieved an AUC of 0.86 in peat swamp forest habitats, reinforcing the utility of GIS-based approaches for elephant conservation. In this study, sensitivity (82.50%) confirmed that most conflict areas were successfully detected, though some remained underpredicted, a limitation also noted by Thant et al. (2023) when elephants occupied marginal habitats. Conversely, the high specificity (94.73%) demonstrated strong exclusion of non-conflict areas, reducing false alarms, while precision (94.29%) confirmed that predicted conflict zones largely matched reality.

The kappa value (0.77) further confirmed substantial agreement beyond chance, consistent with benchmarks from Asian elephant studies (Schwarz et al. 2025, κ: 0.73-0.85). This highlights the robustness of combining confusion matrix metrics with AUC evaluations and supports recent recommendations to report class-specific measures alongside overall accuracy for more comprehensive assessments in applied conservation (Foody 2020).

Contribution of environmental variables

The MaxEnt model identified potential HEC hotspots using georeferenced conflict data and environmental predictors (Table 3). Among these, distance from open land had the highest influence (40.9% contribution, 36.8% permutation importance), highlighting its role in differentiating conflict-prone areas. Distance from settlements contributed moderately (9.2%) but showed the highest permutation importance (38.6%), underscoring its importance in accurately predicting high-risk zones. This suggests that conflicts are most likely where elephants encounter open lands near human activity. Similar patterns have been reported in Aceh (Qomariah et al. 2019) and across South and Southeast Asia (Fernando et al. 2021), where conflicts cluster near settlements in fragmented landscapes. Other anthropogenic variables, distance from roads (8.8%) and plantations (8.3%), also contributed meaningfully, while natural factors such as rainfall, NDVI, elevation, and slope each contributed <1%, reflecting their limited role in the Minas landscape.

Table 2. Cross-validation matrix of HEC model results. The model achieved high overall accuracy (88.46%) and a substantial level of agreement beyond chance (κ: 0.77). User accuracy was highest for conflict areas (94.29%), while producer accuracy was highest for non-conflict areas (94.73%). Sensitivity (82.50%) indicates adequate detection of actual conflict sites, and specificity (94.73%) shows strong reliability in excluding non-conflict zones

Metric	Conflict area	Non-conflict area	Overall	Interpretation
User accuracy (Precision)	94.29%	83.72%	-	High precision for conflict predictions, moderate for non-conflict situations
Producer accuracy (Recall)	82.50%	94.73%	-	Good detection of conflict; very high for non-conflict
Sensitivity (Recall)	82.50%	-	-	Adequate detection of actual conflicts
Specificity	-	94.73%	-	Strong ability to exclude false conflicts
Overall accuracy	-	-	88.46%	High overall predictive reliability
Kappa coefficient (κ)	-	-	0.77	Substantial agreement beyond chance

Table 3. Contribution of environmental variables to HEC prediction. Percent contribution indicates the influence of each variable during model training, while permutation importance measures the decline in model performance when variable values are randomly permuted

Environmental variable	Percent contribution (%)	Permutation importance (%)
Distance from open land	40.9	36.8
Distance from industrial forest plantations (HTI)	22.8	2.5
Distance from the settlement	9.2	38.6
Distance from roads	8.8	6.6
Distance from plantations	8.3	4
Distance from water bodies	5.9	7.9
Distance from agricultural land	2.7	2.4
Rainfall	0.8	0.8
NDVI	0.3	0.1
Slope	0.1	0
Elevation	0.1	0.3

Response curves of environmental variables

In MaxEnt modeling, response curves illustrate the relationship between environmental variables and the probability of Human-Elephant Conflict (HEC) (Figure 6). This study generated curves for five spatial predictors: distance from open land, industrial forest plantations (HTI), settlements, roads, and plantations. The x-axis represents distance (m), while the y-axis indicates predicted conflict probability (0-1) (Phillips et al. 2006; Phillips and Dudík 2008). The curves highlight how proximity to landscape features influences conflict likelihood. Unimodal patterns suggest that conflict risk peaks at intermediate distances, close enough for elephants to access crops yet far enough to avoid disturbance, consistent with findings from Jambi and Aceh (Qomariah et al. 2019; Fikri et al. 2023). Negative exponential curves show higher risk near features such as forest edges or roads, while logistic-like declines indicate threshold distances beyond which risk levels off (Jayakody et al. 2024). U-shaped patterns were also observed, with higher conflict probability at both near and far distances, reflecting shifting elephant behavior in fragmented landscapes (Kuswanda et al. 2022; Rahman et al. 2023; Rendana et al. 2023).

Spatial modeling shows that anthropogenic features—open lands, settlements, industrial forests, roads, and plantations—are major drivers of HEC, with risk patterns shaped by proximity. Areas within 0-2 km of open land pose high conflict risk, as they often serve as movement corridors through fragmented mosaics (Sukmantoro et al. 2019; Imron et al. 2023). Industrial plantation forests (HTI), though dominated by non-preferred species such as *Acacia* and *Eucalyptus*, still attract elephants and create risks of accidental encounters with workers, functioning as alternative refuges (Troup et al. 2020). Conflict risk is also high within 0-1 km of settlements, where fragmentation forces elephants closer to villages and crops (Hadinata et al. 2023; Ningrum et al. 2023). Roads amplify conflict within 500 m due to traffic, disturbance, and access pressures, while plantations within 0-2 km trigger repeated crop-raiding as elephants exploit accessible food sources (Troup et al. 2020; Rachmawaty et al. 2022).

HEC potential model

The spatial model developed using the MaxEnt algorithm effectively predicted the potential risk zones for human-elephant conflict (HEC) across the study area (Figure 7). The probability output from the model ranged from 0 to 1, which was reclassified into ten probability intervals expressed as percentages, following the approach of Qomariah et al. (2019). These intervals reflect varying levels of HEC probability (Figure 6), from minimal to very high risk (Table 4).

This study mapped the spatial distribution of HEC risk, highlighting priority areas for mitigation and conservation. High-risk zones (70-100% probability) covered 19.94 km² (1.76% of the landscape) and represent critical priorities due to their high likelihood of conflict. Moderate-risk zones (40-70%) spanned 40.60 km² (3.57%) and serve as transitional areas and extensions of elephant corridors. Low-risk zones (10-40%) encompassed 221.32 km² (19.48%) and require monitoring given shifting ecological and social pressures. The majority of the landscape, 854.02 km² (75.19%), fell within the minimal-risk category, functioning as safe zones for human communities but still vulnerable to future land-use or climate change.

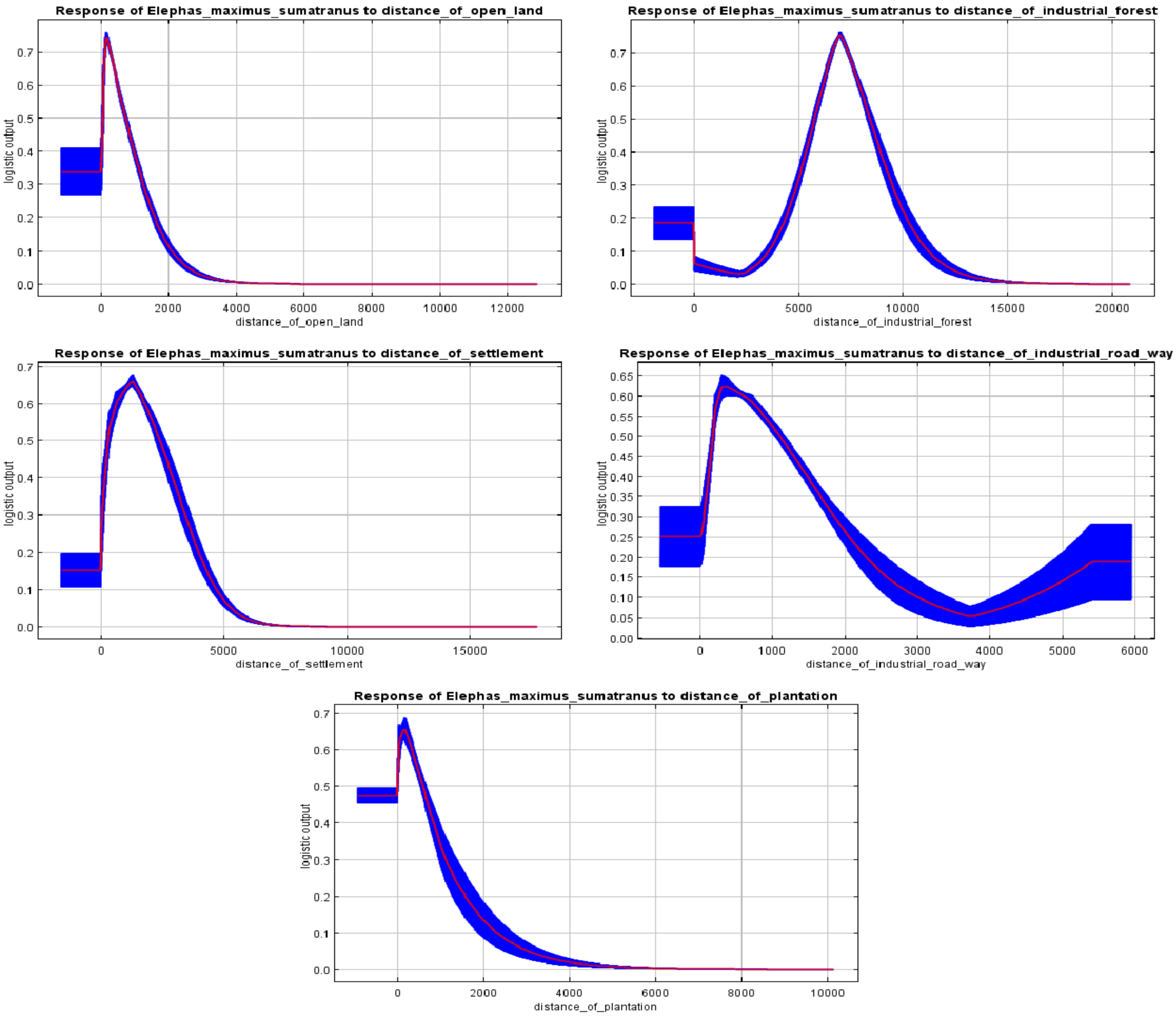


Figure 6. Response curves show how HEC suitability varies with distance from open land, HTI, settlements, roads, and plantations. The red line represents the mean model response, with blue shading indicating ±1 standard deviation. Results reveal the highest probability of elephant presence near settlements, plantations, and roads, decreasing with distance, underscoring the strong influence of edge habitats and human-modified features on conflict risk

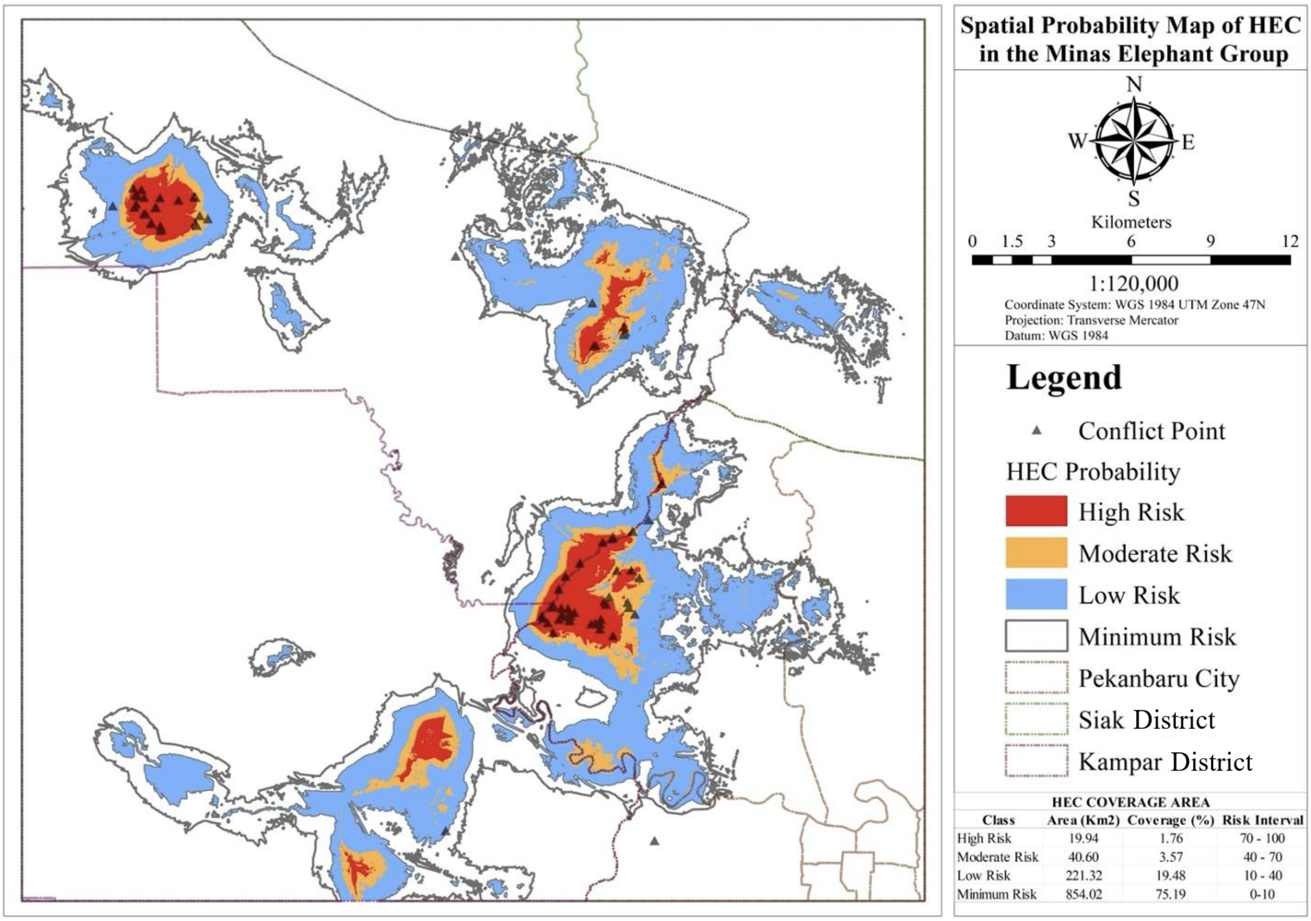
Table 4. Classification of HEC risk based on probability values. The table displays predicted conflict probability classes, corresponding spatial coverage (in km² and %), and associated risk levels. High-risk zones (≥70% probability) cover only ~1.8% of the landscape but represent priority areas for targeted mitigation, while the majority of the area (≥75% coverage) falls within very low to minimal risk zones

HEC probability (%)	Area (km^2)	Coverage %	Classification	Risk level
90-100%	5.92	0.52	Very high risk, priority for mitigation	High
80-90%	5.98	0.53	High risk, requires serious intervention	High
70-80%	8.04	0.71	Moderately high risk, needs close monitoring	High
60-70%	10.50	0.92	Medium to high risk	Moderate
50-60%	12.56	1.11	Medium risk, moderate conflict potential	Moderate
40-50%	17.54	1.54	Medium to low risk	Moderate
30-40%	27.93	2.46	Low to medium risk	Low
20-30%	53.09	4.67	Low risk	Low
10-20%	140.30	12.35	Very low risk	Low
0-10%	854.02	75.19	Minimal conflict zone	Minimum
Total	1135.89	100	Total area	

High-risk zones were concentrated near elephant core habitats, traditional movement corridors, and areas of intense human activity such as plantations, settlements, and roads. These ecologically sensitive areas function as key crossing points where human-elephant interactions are most frequent. Habitat fragmentation and the expansion of cultivated lands further intensify conflict in migration corridors, potentially altering elephant behavior and undermining their ecological role as seed dispersers and forest regenerators (Natarajan et al. 2025). As such, targeted interventions in these high-risk areas are essential, in line with risk-based strategies for Asian elephants (Williams et al. 2020; Thant et al. 2023).

Moderate-risk zones serve as transitional landscapes and movement corridors that are critical for maintaining habitat connectivity in fragmented ecosystems. Land-use change and habitat loss have historically driven the decline of elephant populations across Asia, making these areas vital for sustaining ecological linkages (de Silva et al. 2023). Evidence from Bengkulu shows that elephant movements are strongly influenced by proximity to roads and water sources, highlighting the importance of moderately pressured areas as functional corridors (Laksmitha et al. 2023). These spaces not only support elephant mobility but also provide connectivity for other large mammals, including the Sumatran tapir and tiger (Rahman et al. 2022).

Low-risk zones indicate relatively low potential for conflict but should be interpreted cautiously given the dynamic nature of elephant movements and ongoing land-use changes. These areas may become substitute habitats when pressures increase in core zones. For instance, secondary vegetation growth or the expansion of oil palm plantations can shift elephant ranges (Evans et al. 2020). Connectivity analyses in Sumatra show that many suitable patches lie adjacent to existing ranges, allowing elephants to move quickly into neighboring low-conflict areas when disturbed (Imron et al. 2023). Experts therefore emphasize fostering human-elephant coexistence in such buffer landscapes (de la Torre et al. 2021). Moreover, predictive modeling suggests that HEC hotspots may shift by 2050 due to climate and land-use changes, underscoring the need for proactive mitigation even in currently tranquil zones (Guarnieri et al. 2024).



HEC COVERAGE AREA

Class	Area (Km2)	Coverage (%)	Risk Interval
High Risk	19.94	1.76	70 - 100
Moderate Risk	40.60	3.57	40 - 70
Low Risk	221.32	19.48	10 - 40
Minimum Risk	854.02	75.19	0-10

Figure 7. Potential locations for HEC. The legend indicates the potential for HEC in percentage terms. The higher the number, the higher the potential for the area to have HEC. The table data on the right below classifies the risk interval as high, moderate, low, and minimal risk, which potentially causes HEC in this study area

Minimal-risk zones, which dominate the landscape, likely reflect unsuitable habitat, limited human access, or the absence of elephant populations. These areas often lack the ecological features needed to support elephants, such as water sources, vegetation cover, or migration paths. However, they should not be assumed conflict-free. Future pressures, such as climate change, agriculture, and infrastructure expansion, may push elephants into these areas (Beirne et al. 2020). From a conservation standpoint, minimal-risk zones hold potential as future ecological reserves. Long-term restoration and improved connectivity could transform currently unoccupied multi-use landscapes into viable elephant habitats (Rahman et al. 2022).

HEC by land cover and broader implications

The overlay analysis between conflict points and land-cover types in Minas, Riau, revealed that most incidents occurred in settlements, shrublands, and plantations (Table 5). This indicates that conflicts are concentrated in human-modified landscapes where community livelihoods intersect with elephant foraging and movement routes (Wadey et al. 2018; Lim and Campos-Arceiz 2022). High incidences in settlements highlight the socio-economic vulnerability of rural communities, while frequent cases in shrubland and plantation areas underscore elephants' reliance on secondary vegetation and cultivated habitats when primary forests are degraded or inaccessible (Abdullah et al. 2019; Beirne et al. 2020; Lesmana and Saam 2024).

These spatial patterns mirror findings across tropical Asia, where habitat conversion and fragmentation consistently elevate human-elephant conflict. In India, conflicts intensified around Buxa Tiger Reserve following forest conversion to farms and settlements (Nad et al. 2021), while Singh et al. (2023) documented an elevenfold expansion of elephant range into agricultural land in West Bengal. In Sri Lanka, nearly all conflict events occurred within one kilometer of land-cover change zones (Rathnayake et al. 2022), and over half were concentrated near open forests and forest boundaries (Gunawansa et al. 2023). Comparable cases are reported in Xishuangbanna, China, where degraded habitats near reserve edges hosted the highest conflict rates (Tang et al. 2024), and in northern Tanzania, where elephants accelerated their movements through settlements instead of avoiding them (Sanare et al. 2022).

Similar dynamics are also observed in another megafauna in Sumatra. Human-tiger conflict is heavily clustered in settlements and plantations, with up to 86% of cases occurring in villages and farms rather than forest edges (Widodo et al. 2022; Lubis et al. 2023). The critically endangered Sumatran rhinoceros faces heightened risks such as encroaching farms and settlements fragmenting its remaining habitats, increasing the likelihood of crop raiding and human encounters (Pusparini et al. 2015).

In response to escalating HEC in Minas, several mitigation strategies have been implemented, most notably the reactivation of the PLG Minas by the BBKSDA Riau. This initiative utilizes trained semi-captive elephants to guide wild elephants away from human settlements and redirect them toward forested areas. Similar approaches have been adopted in the Flying Squad program, operated by the World-Wide Fund for Nature Organization (WWF), in Tesso Nilo National Park (Tohir et al. 2016), reflecting a growing institutional emphasis on non-lethal, behavior-based deterrence strategies. However, these efforts remain geographically limited by operational and financial capacities. The lack of scalable, community-based, and ecologically informed interventions hinders the development of a long-term conflict mitigation framework (Shaffer et al. 2019; de la Torre et al. 2021; Kochprapa et al. 2024).

MaxEnt modeling of the Minas Elephant Group's movement patterns during 2020-2021 confirms the study's hypothesis that HEC is most likely to occur in areas close to built-up zones and regions with intensive human activity. The model achieved high predictive accuracy, with an AUC value of 0.954, indicating strong reliability in identifying spatial risk gradients. Among the tested predictors, distance to open land and industrial forest plantations emerged as the most influential variables driving HEC probability. Spatial analysis revealed that the highest conflict risk zones, classified within the 70-100% probability range, covered an area of 19.94 km² (1.76% of the total area), while moderate-risk regions (40-70% probability) spanned 40.60 km² (3.57%). These zones are not preferred habitats for elephants, but they are traversed as movement corridors connecting fragmented habitat patches. This spatial pattern reflects increasing landscape fragmentation, which forces elephants to move across human-modified zones to fulfill their ecological needs. Conversely, low- and minimum-risk areas account for over 90% of the landscape, highlighting a significant spatial imbalance between high-risk zones and the broader matrix.

These findings underscore the need for adaptive mitigation strategies that prioritize high- and moderate-risk areas, despite their limited extent, as key zones of human-elephant conflict. Low-risk areas should be preserved as ecological buffers to maintain connectivity and reduce conflict. Short-term actions include installing warning signs in open lands, especially along TSSH ecotones and riparian corridors, as well as fencing and surveillance around new oil palm plantations within elephant ranges.

Table 5. Distribution of HEC points across different land-cover types. Settlement areas accounted for the highest proportion, followed by shrubs, plantations, and HTI

Land cover type	Number of conflict points	Percentage (%)
Agriculture	5	6.41
Industrial Forest Plantations (HTI)	6	7.69
Open land	1	1.28
Plantation	13	16.67
Secondary forest	1	1.28
Settlement	29	37.18
Shrubs	22	28.21
Water body	1	1.28
Total	78	100

Long-term efforts must prioritize ecological corridors to reconnect fragmented herds, particularly the Minas and Giam Siak Kecil populations, to ensure genetic viability and reduce spatial stress. However, the current MaxEnt model is limited by the absence of fine-scale anthropogenic variables (e.g., human population density, activity intensity) and lacks detail on forage type and nutritional quality, with NDVI used only as a proxy. Future research should integrate ecological and social factors to improve predictive accuracy and support spatially adaptive HEC policies. It is also recommended that BBKSDA Riau systematically record material and human losses to enable regular monitoring and evaluation of conflict impacts.

Limitations of the spatial risk model

This study has several limitations. First, the spatial analysis was confined to the home range of Elephant Group 11 (Minas group) using GPS collar data from 2020-2021, which may not represent wider temporal or spatial conflict patterns. Seasonal variation was not explicitly analyzed, limiting the generalizability of temporal findings. Community-reported conflict data may contain recall bias, and although validated where possible with timestamped GPS data, some uncertainty remains. Ground verification was constrained by safety and access challenges, preventing full on-site validation. In addition, industrial plantation areas such as HTI and private oil palm concessions were excluded due to permit restrictions. Finally, reliance on presence-only data restricts the ability to model absence or conflict intensity. Therefore, the resulting maps should be viewed as indicative tools, requiring ongoing ground-truthing, adaptive monitoring, and integration with local knowledge for effective management.

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